RevDedup: A Reverse Deduplication Storage System Optimized for Reads to Latest Backups

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Abstract

Scaling up the backup storage for an ever-increasing volume of virtual machine (VM) images is a critical issue in virtualization environments. While deduplication is known to effectively eliminate duplicates for VM image storage, it also introduces fragmentation that will degrade read performance. We propose *RevDedup*, an inline deduplication system that optimizes reads to latest VM image backups using an idea called reverse deduplication. In contrast with conventional deduplication that removes duplicates from new data, RevDedup removes duplicates from old data, thereby shifting fragmentation to old data while keeping the layout of new data as sequential as possible. We evaluate our RevDedup prototype using microbenchmark and real-world workloads. For a 12-week span of real-world VM images from 160 users, RevDedup achieves high deduplication efficiency with around 97% of saving, and high backup and read throughput on the order of 1GB/s. RevDedup also incurs small metadata overhead in backup/read operations.

1 Introduction

Many enterprises today adopt virtualization technologies to run a large number of virtual machines (VMs) on a small group of physical hosts. For disaster recovery, it is necessary to preserve user data and any operating system updates made to a VM. Conventional approaches schedule backups for each VM disk image and keep different versions of each VM backup, so that administrators can restore any previous recovery checkpoint. Today's backup solutions are mainly based on disk-based storage, which has better I/O performance than traditional tape-based storage. However, each VM image typically contains several gigabytes of data. Even though the cost of disk-based storage is low nowadays, in the face of a large volume of VMs and a large volume of versions associated with each VM, scaling up the backup storage for VM images still remains a critical deployment issue.

Deduplication improves storage efficiency by eliminating redundant data. Instead of storing multiple copies of data blocks that have identical content, a deduplication system stores only one copy of identical blocks, while other blocks refer to the copy via smaller-size references. Deduplication is mainly studied in content-addressable backup systems (see §2.2). It is also shown to provide space-efficient VM image storage given that VM images have significant content similarities [10, 11, 15, 19].

Most existing deduplication studies focus on optimizing storage efficiency and write (or backup) performance. However, one drawback of deduplication is that it introduces *fragmentation*, since some blocks of a file may now refer to other identical blocks of a different file. Hence, accessing a file is no longer sequential as in ordinary file systems without deduplication, but instead requires additional disk seeks to the identical blocks being referenced. This significantly degrades read performance. On the other hand, we believe that

achieving high read throughput is necessary in any backup system. For instance, a fast restore operation can minimize the system downtime during disaster recovery. Also, enabling high read performance makes new applications feasible. For example, administrators can retrieve recently archived VM images to conduct forensic analysis.

In this work, we explore the use of deduplication for VM image backup storage on a disk-based backend. Our goal is to maintain high read throughput as in ordinary file systems without deduplication, while maintaining high write performance and high storage efficiency as in existing deduplication systems. We focus on *inline* deduplication, meaning that deduplication is performed on the write path. In practice, users are more likely to access more recent data. Our key insight is that traditional inline deduplication systems check if new blocks can be represented by any already stored blocks with identical contents. Thus, the fragmentation problem of the latest backup is the most severe since its blocks are scattered across all the prior backups. To mitigate fragmentation in newer backups, we propose to do the opposite, and check if any already stored blocks can be represented by the new blocks to be written. We remove any duplicate blocks that are already stored so as to reclaim storage, and refer them to the new blocks. This shifts the fragmentation problem to the older backups, while keeping the storage layout of the newer backups as sequential as possible. We call this *reverse deduplication*, which is the core component of our deduplication design.

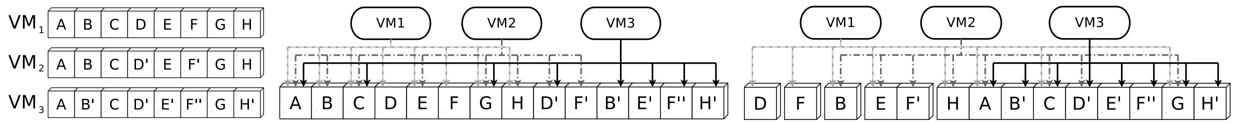
To this end, we propose *RevDedup*, an inline deduplication system designed for VM image backup storage. RevDedup exploits content similarities of VM images in two levels. It applies coarse-grained global deduplication to different VMs, and further applies fine-grained reverse deduplication to different backup versions of the same VM. We propose a configurable, threshold-based block removal mechanism that combines *hole-punching* [17] to remove duplicate blocks of old backup versions and *segment compaction* to compact data segments without duplicate blocks to reclaim contiguous space.

We implement RevDedup based on a client-server model, which allows multiple clients to submit changes of VM images to a storage server. We experiment our RevDedup prototype on a RAID disk array using microbenchmark and real-world workloads. In particular, we collected a dataset of weekly VM image snapshots for 160 university students in a computer science programming course over a 12-week span. We show via this dataset that RevDedup achieves (i) high deduplication efficiency with around 97% of saving, (ii) high write throughput at 4-7GB/s, and (iii) high read throughput for the latest backup at 1.2-1.7GB/s. We also show that conventional deduplication experiences throughput drop when retrieving newer backups. Finally, we show that RevDedup incurs small metadata overhead in backup/read operations when it operates on a VM backup with a large number of versions. To our knowledge, this is the first work that provides prototype implementation of a deduplication storage system that is optimized for reads to latest backups.

The rest of the paper proceeds as follows. In §2, we discuss the fragmentation problem in deduplication and review related work. In §3, we describe the design and implementation of RevDedup. In §4, we present experimental results. Finally, in §5, we conclude the paper.

2 Background and Motivation

Deduplication is a well-known technique for exploiting content similarities and eliminating the storage of redundant data. Typical deduplication systems divide a backup stream into *blocks*, and use *fingerprints* to identify blocks and check if blocks can be deduplicated. A fingerprint is computed by a cryptographic hash (e.g., MD5, SHA-1) of the content of a block. Two blocks are said to be identical if their fingerprints are the same. We assume that the probability that two different blocks have fingerprint collisions is negligible [3].



(a) Backups (b) Conventional deduplication (c) RevDedup

Figure 1: An example of how conventional deduplication and RevDedup place data on disk.

2.1 Fragmentation

Most deduplication systems suffer from the inherent fragmentation problem, which has also been addressed in prior work [12, 18, 25, 27]. We now illustrate the fragmentation problem using a simple example. Figure 1(a) shows that a deduplication system is about to write, in order, three snapshots of a VM, denoted by VM_1, VM_2, and VM_3. We assume that each VM image has eight blocks, and that the system has no data initially. Figure 1(b) shows how a conventional deduplication system writes data. First, the system writes VM_1 with unique blocks A to H. Given that all blocks are new, the system will sequentially write all of them to disk. Next, the system writes VM_2, in which some of the blocks are identical to those of VM_1. Then the system stores only the references that refer to those identical blocks, and appends the unique blocks D' and F' to the end of the last write position. The same approach applies when the system writes VM_3, and it only writes the unique blocks E', F", and H' to the end of the last write position.

From Figure 1(b), we see that the blocks of the latest written image VM_3 are re-ordered and randomly scattered across the previously written images VM_1 and VM_2. Reading VM_3 will generate disk seeks and see degraded performance. We can perform simple calculation to understand the degradation. Consider a generic 7200 RPM 3.5-inch SATA harddisk with an average seek time of 8.5ms [26]. With only 60 disk seeks per second on the read path, the read throughput can drop by at least 50% compared to the sequential read (which we assume has negligible seek time).

Maintaining high read performance for deduplication backup systems is necessary for minimizing the system downtime during disaster recovery (see §1). We note that the latest backup contains the "hot" data and is expected to be more likely read in practice, while older backups contain "cold" data that usually serves the compliance purpose and is less likely read. This guides our design of RevDedup. Figure 1(c) shows the disk layout for the previous example when RevDedup is used. We allow the blocks of VM_3 (i.e., the latest backup) to be sequentially placed on disk. Also, VM_2 is less fragmented than VM_1, in the sense that the blocks of VM_2 are less spread out on disk than those of VM_1. Thus, the newer a backup is, the less fragmentation overhead the backup will experience. We explain how we achieve this property in §3.

2.2 Related Work

Deduplication has been widely used in backup applications. We review related work on deduplication storage.

Deduplication for backup storage. Most existing deduplication studies for backup storage focus on optimizing fingerprint indexing to achieve high backup performance. Deduplication is first proposed in Venti [23] for data backup in content-addressable storage systems. DDFS [31] and Foundation [25] use Bloom-filter-based [4] indexing structures to minimize memory usage. DDFS further exploits spatial locality to cache the fingerprints of blocks that are likely written later. Other studies [2, 9, 13, 16, 30] exploit workload characteristics to reduce memory usage for indexing.

The above studies aim to achieve high write throughput, low memory usage, and high storage efficiency, but put limited emphasis on read performance. One closely related work to ours is by Kaczmarczyk *et al.* [12], who also improve read performance for latest backups in deduplication. Their system selectively rewrites deduplicated data to disk to mitigate fragmentation, and removes old rewritten blocks in the

background. However, they consider deduplication for different versions of a single backup only, while we enable global deduplication across multiple VMs. Nam *et al.* [18] propose a system that measures the fragmentation impact given the input workload and activates selective deduplication on demand. Instead of selectively rewriting duplicates as in both studies [12,18], we use a completely different design by removing duplicates of old data to maintain high deduplication efficiency. Our design inherently makes older (newer) backups more (less) fragmented. Note that both studies [12,18] only conduct simulation-based evaluations, while we implement a prototype to experiment the actual I/O throughput.

Distributed deduplication. DeDe [5] targets a storage area network (SAN) connecting multiple client hosts that run VM instances. It performs out-of-order deduplication in the hosts to minimize the synchronization overhead. Our work also considers multiple clients, yet we focus on inline deduplication. HYDRAstor [6] and its successor HydraFS [29] are distributed deduplication systems with multiple storage nodes. Our work focuses on a single storage backend.

Deduplication for primary storage. Several file systems (e.g., [7,14,20–22]) deploy inline deduplication for primary storage. In particular, iDedup [27] is a primary, inline deduplication system that optimizes read performance. It applies deduplication to chains of duplicate 4KB blocks of some predefined length. For each block to be written, it searches for all candidate block chains containing the block and identifies the longest chain for deduplication. iDedup targets primary workloads rather than separate backup images, so it has different design requirements. Specifically, it does not specifically optimize reads to latest data like ours.

Version control systems. Our work in essence provides similar functionalities as in traditional version control systems. Rdiff-backup [24] and Subversion [1] generate changes between adjacent versions on a per-file basis. In particular, Subversion improves restore performance via a skip-list data structure. Both studies do not address global deduplication as in our work. Git [8] enables global deduplication, but only in the whole-file level rather than the more fine-grained block level.

3 RevDedup

RevDedup is an inline deduplication system for backing up the disk states of multiple VMs. It builds on a client-server model similar to prior studies [5, 9]. In RevDedup, a server stores deduplicated VM disk images and the deduplication metadata, while multiple clients run the active VMs operated by different users. The server provides an interface for each client to backup and restore specific VM images; the clients take snapshots of VM disk images, compute fingerprints on the snapshots, and upload the snapshots and fingerprints to the server.

RevDedup considers a single snapshot created from the disk image of a VM as a backup. We call different snapshots that belong to the same VM to be *versions*. RevDedup is designed to store and retrieve multiple versions of different VMs in a virtualization environment.

Goals. RevDedup aims to achieve several goals:

- *Storage efficiency:* It achieves high deduplication efficiency and effectively reduces redundant storage of VM images.
- *Memory usage:* It uses limited memory usage for deduplication indexing.
- *Backup*: It achieves high backup throughput of multiple backup streams given the available resources in the system.
- *Restore:* It achieves near raw disk throughput in restoring the latest versions of any VMs.

In this section, we elaborate how RevDedup achieves the above goals. First, to mitigate fragmentation on the read path, RevDedup applies *coarse-grained global deduplication* to amortize disk seeks over large-size

data units (see §3.1). Also, to maintain high deduplication efficiency, RevDedup further applies *fine-grained reverse deduplication*, in which we maintain the data placement as sequential as possible for the latest version, while removing any redundant data of the old versions and referring it to the identical data of the latest version. This achieves high deduplication efficiency, and in the meantime mitigates fragmentation and achieves high read performance for the latest version (see §3.2). To improve scalability, our RevDedup implementation offloads part of the deduplication workload from the server to multiple clients and allows multiple clients to submit versions concurrently to the server (see §3.3). We also discuss how RevDedup differs from conventional deduplication in backup/read performance (see §3.4).

Assumptions. We assume that RevDedup applies fixed-size chunking to backup streams, i.e., we divide data into fixed-size units each identified by a fingerprint, and determine if the unit can be deduplicated. Fixed-size chunking shows significant storage savings for VM images [10, 11], while having smaller chunking overhead than variable-size chunking.

We also assume that both RevDedup client and server processes run in user space and are deployed in Linux. The storage backend of the server is mounted on a Linux native file system (e.g., Ext4 and XFS). We leverage some available functionalities of Linux in our design.

Furthermore, RevDedup assumes that the stored data will never be deleted. The issues of performing garbage collection on deleted versions are posed as future work.

3.1 Coarse-Grained Global Deduplication

The first approach that RevDedup uses to mitigate fragmentation is to apply coarse-grained global deduplication to the pool of the already stored VM snapshots (we discuss additional approaches in §3.2). By coarse-grained, we mean that RevDedup applies deduplication to large fixed-size units called *segments*, each of which has a size of several megabytes. By global, we mean that we apply deduplication to all versions and eliminate duplicate segments that appear (i) in the same version, (ii) in different versions of the same VM, or (iii) in different versions of different VMs. Each segment is identified by a fingerprint that is generated from the cryptographic hash of the segment contents.

Our rationale of using large-size segments as our global deduplication units is as follows. We expect that the content of a segment is sequentially written to disk, and a disk seek occurs only if consecutive segments of a VM image are not adjacently stored on disk due to deduplication. With a large segment size, the disk seek time of locating segments only forms a small portion of the total time of reading all segment contents of a VM image. Thus, we effectively mitigate fragmentation by amortizing disk seeks over large-size segments [13, 27].

Evaluations on our real-world dataset (see §4.2) show that using large-size segments for global deduplication can still achieve high deduplication efficiency (with at least 80% of space saving). One possible reason is that files in a VM image are sequentially placed. Changes of user files are likely aggregated in a small region, while the operating system files remain intact. Thus, the content differences of two versions of the same VM are clustered in a small region of the VM image, and a substantial portion of segments will remain the same.

Nevertheless, we point out that using large-size segments in deduplication cannot maintain the same level of deduplication efficiency as in existing fine-grained deduplication approaches. We address this in §3.2.

3.1.1 Indexing

The server holds a global deduplication index that keeps track of the fingerprints and other metadata of all segments. By using large-size segments, the server can hold a small index that can be fit into memory. We justify this claim using a simple example. Suppose that the segment size is 8MB (a parameter used in our

evaluation). For each petabyte of storage, we have to index 128 million entries. Suppose that the size of each entry is 32 bytes, which we believe suffice to store the fingerprint (e.g., 20 bytes for SHA-1) and other metadata for each segment. Then the index consumes a total size of 4GB, and can be fit into memory of today's commodity hardware.

3.2 Fine-Grained Reverse Deduplication

In addition to segment-level deduplication, RevDedup also applies more fine-grained deduplication on a sub-segment level to further eliminate duplicates. We define smaller fixed-size sub-segments called *blocks*, each of which has a size of several kilobytes. For example, the deduplication block size can be set as the disk block size (e.g., 4KB) of native file systems. Like segments, each block is identified by a fingerprint given by the cryptographic hash of the block content.

RevDedup builds on a novel idea called reverse deduplication, which mitigates fragmentation due to block-level deduplication in two ways. First, reverse deduplication is only local, meaning that it is only applied to different versions of the same VM. This avoids incurring disk seeks across the versions of different VMs. Second, and most notably, reverse deduplication removes duplicate blocks of old versions and refers them to the blocks of new versions. This reduces the disk seeks of reading the latest version of a VM and shifts the fragmentation overhead to older versions.

3.2.1 Indexing

Before discussing how reverse deduplication works, we first describe how we perform indexing on block-level deduplication. Each segment can be retrieved from disk using the in-memory index (see §3.1.1). It is associated with a metadata file that is identified by the segment fingerprint. The metadata file keeps the block fingerprints of all blocks associated with the segment. All metadata files are stored on disk.

For each version to be stored, RevDedup builds the index on the fly by loading the metadata files of all segments into memory, and use this index for block-level deduplication. To quantify the memory usage, consider the following parameters used in our evaluation, such that the total size of a VM image is 7.6GB, the block size is 4KB, and each block-level index entry is 32 bytes. Since reverse deduplication operates by comparing similarities of two versions of VM images (see below), the total memory usage is up to $2\times7.6\text{GB}\div4\text{KB}\times32$ bytes $=121.6$MB. The actual memory usage can be further reduced if we do not store the fingerprints of null (zero-filled) blocks. Also, if two segments are identical, their associated blocks must also be identical and hence we do not need to load their block fingerprints into memory. Note that the index only temporarily resides in memory and will be discarded after we finish deduplication for the version to be stored.

As long as the VM image size is on the order of tens of gigabytes, the memory usage of our indexing approach is feasible with today's commodity hardware. However, the memory usage increases proportionally with the VM image size. One solution to reducing memory usage is to build the Bloom-filter-based [4] index structure as in prior studies [25, 31]. We pose this issue as future work.

3.2.2 Reverse Deduplication on Unique Segments

We first consider how reverse deduplication operates on different versions of a single VM, assuming that all segments are unique and there is no global deduplication across segments. Note that different unique segments may still share identical blocks.

Figure 2 shows how reverse deduplication works, based on the example shown in Figure 1. Each version contains a number of block pointers, each of which holds either a *direct reference* to the physical block content of a segment, or an *indirect reference* to a block pointer of a future version. An indirect reference

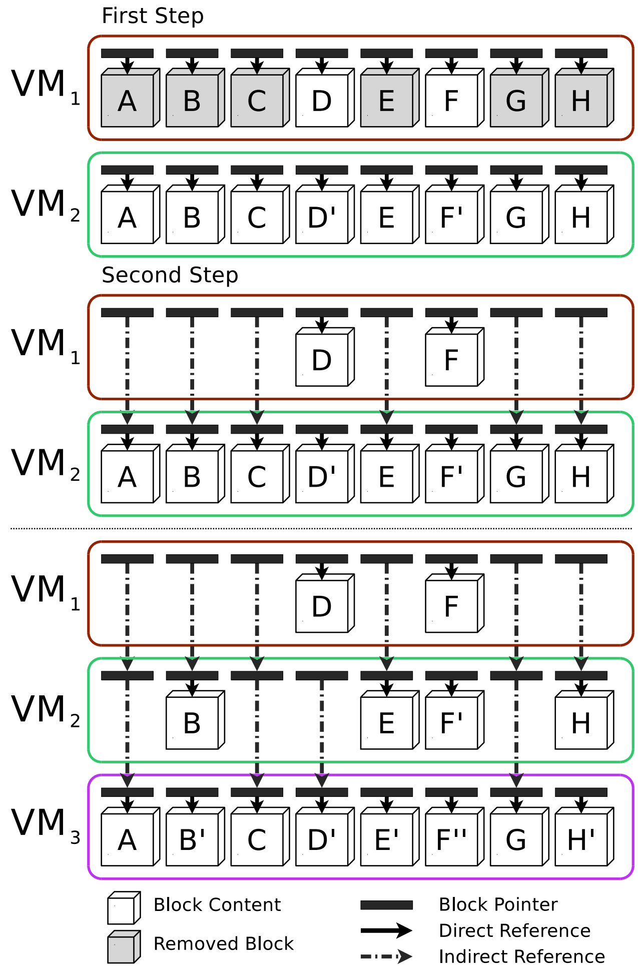


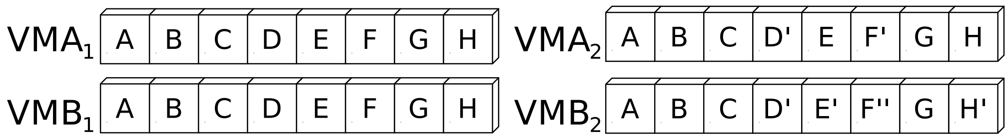
Figure 2: An example of reverse deduplication for multiple versions of the same VM.

indicates that the block can be accessed through some future version. In RevDedup, any latest version of a VM must have all block pointers set to direct references.

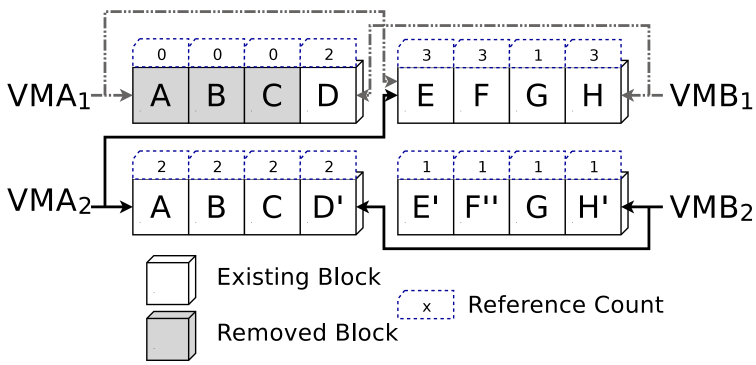
Suppose that the system has already stored a version VM_1, and now a new version VM_2 of the same VM is submitted to the system. We compare VM_1 and VM_2 by loading all their block fingerprints from disk. If a matched block is found in both VM_1 and VM_2, we remove the respective block of VM_1, and update that block with an indirect reference that refers to the identical block of VM_2. Now if we write another version VM_3 of the same VM, we compare its blocks with those of VM_2, and remove any duplicate blocks of VM_2 as above. Some blocks of VM_1 are now referred to those of VM_3. To access those blocks of VM_1, we follow the references from VM_1 to VM_2, and then from VM_2 to VM_3.

In general, when writing the ith version VM_i, we compare the block fingerprints of VM_i with those of the previous version VM_{i-1}. We remove any duplicate blocks of VM_{i-1} and update the block pointers to refer to the identical blocks of VM_i. To simplify the deduplication process, one key assumption we make is that we only compare with the most recent version. Hence, we may miss the deduplication with the redundant blocks of earlier versions (i.e., VM_{i-2}, VM_{i-3}, $\cdots$, etc.). Nevertheless, the analysis of our real-world dataset (see §4.2) indicates that such misses only contribute 0.6% of additional space usage. Thus, RevDedup still achieves high deduplication efficiency with this assumption.

When reading the ith version VM_i, we either follow the direct reference to access the physical block, or a chain of indirect references to future versions (i.e., VM_{i+1}, VM_{i+2}, $\cdots$, etc.) until a direct reference is hit.



(a) VM versions



(b) Reference counts

Figure 3: An example that shows how reference counts are assigned when reverse deduplication is applied to shared segments.

We point out that tracing the indirect references incurs only small overhead in the read operation (see §4).

3.2.3 Reverse Deduplication on Shared segments

When segment-level global deduplication is in effect, we cannot directly remove a block whose associated segment is shared by other versions or within the same version. RevDedup uses *reference counting* to decide if a block can be safely removed. We associate each block with a reference count, which indicates the number of direct references that currently refer to the block among all versions of the same VM or different VMs. The block reference counts are kept inside the metadata files associated with the segments. Figure 3 shows an example of how reference counts are used. Suppose that two VMs, namely VMA and VMB, are stored. Let the segment size be four blocks. The first versions VMA_1 and VMB_1 have the same set of blocks. For the second versions, VMA_2 has new blocks D' and F', while VMB_2 has new blocks D', E', F", and H'. We see that any blocks with zero reference counts (in the segment ABCD) can be safely removed.

With reference counting, we now describe the complete reverse deduplication design. When a client writes the ith version VM_i of a VM, the server first applies global deduplication with the segments of other VMs. For each segment of VM_i, if it is unique, then the reference counts of all associated blocks are initialized to one; if the segment can be deduplicated with some existing segment, then the reference counts of all associated blocks of the existing segment are incremented by one. Next, the server loads all the block fingerprints of VM_{i-1} (the previous version) and VM_i into memory. It applies reverse deduplication and compares the block fingerprints of VM_{i-1} and VM_i. If a block of VM_{i-1} can be deduplicated with some block of VM_i, then the block of VM_{i-1} will have its reference count decremented by one and its direct reference updated to an indirect reference that refers to the block of VM_i. If the reference count reaches zero, it implies that the block (of VM_{i-1}) is not pointed by any direct references, but instead can be represented by the same block of future versions. It can thus be safely removed.

3.2.4 Removal of Duplicate Blocks

RevDedup operates by removing duplicate blocks from segments. We consider two block removal approaches, namely block punching and segment compaction. To this end, we propose a configurable mechanism that combines both approaches.

Block punching. We leverage the hole-punching mechanism available in Linux Ext4 and XFS file systems [17], where we can issue in user space the system call `fallocate(FALLOC_FL_PUNCH_HOLE)` to a file region. Any file system block covered by the hole-punched region will be deallocated and have its space released. The respective block mappings of the file will be updated in the file system.

Segment compaction. Segment compaction is to compact a segment that excludes the removed blocks. It operates by copying all blocks of a segment, except those that are to be removed, sequentially into a different segment. The original segment will be deleted and have its space released, and the new segment is kept instead.

Threshold-based block removal. Block punching involves file system metadata operations. If the number of removed blocks is small, block punching is expected to incur small overhead. However, block punching has a drawback of introducing disk fragmentation *(note that it is different from the fragmentation problem in deduplication we discussed)*, as non-contiguous free blocks will appear across disk. This degrades write performance when the amount of disk usage is close to its raw capacity. On the other hand, segment compaction mitigates disk fragmentation as it copies all remaining blocks in sequence. However, if the number of removed blocks is small, it has large I/O overhead since it reads and writes the actual data content of the non-removed blocks. Therefore, we propose a threshold-based block removal mechanism, which uses a pre-defined threshold (called the *rebuild threshold*) to determine how to rebuild a segment excluding removed blocks. If the fraction of blocks to be removed from a segment is smaller than the rebuild threshold, then block punching will be used; otherwise, segment compaction will be used. The rebuild threshold is configured to trade between disk fragmentation and segment copying time. We evaluate the impact of the rebuild threshold in §4.

Note that after we remove some blocks from a segment, no more blocks will be further removed from the same segment. In other words, we only apply block removal (via either block punching or segment compaction) to a segment *at most once* only. If a segment contains blocks with zero reference counts, it implies that no latest versions refer to the segment. For example, from Figure 3, when we remove blocks from the segment ABCD, only the old versions VMA_1 and VMB_1 refer to it. When we upload future versions of VMA (or VMB), the segment will no longer be compared, while only the segments referenced by the latest version VMA_2 (or VMB_2) will be considered.

3.3 Implementation

Our RevDedup implementation builds on the client-server model as shown in Figure 4. RevDedup uses client-side deduplication to reduce the client-server communication overhead. When a client is about to submit a version of a VM to the server, it first divides the VM image snapshot into different segments and computes both segment-level and block-level fingerprints for the version. Next, the client queries the server, using the segment fingerprints, whether the segments are already stored in the server. If any segment has already been stored, then the client discards the upload of that segment. The client then uploads the unique segments to the server (e.g., via RESTful APIs). It also sends the metadata information, including all segment and block fingerprints for the whole VM image and the information of the version (e.g., the VM that it belongs, the size of the image, etc.). Note that we offload the server by having the clients be responsible for both segment and block fingerprint computations. This avoids overloading the server when it is connected by too many clients.

Upon receiving the unique segments and metadata information of a version, the server writes them to

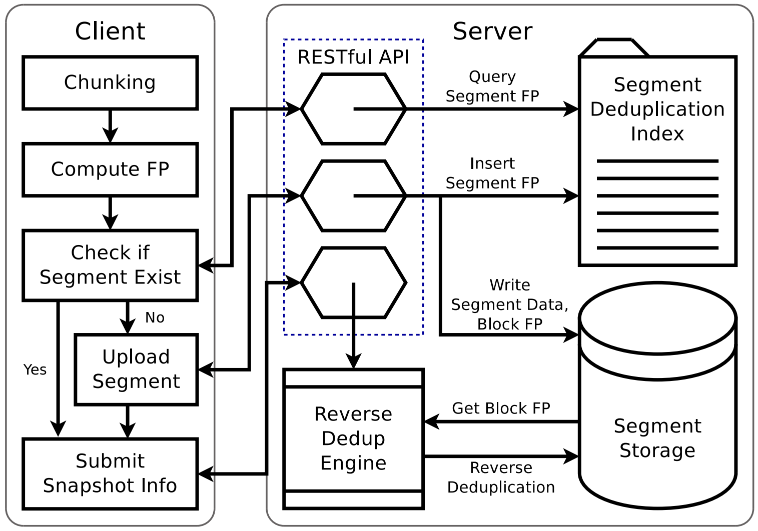


Figure 4: RevDedup's client-server model.

disk and links the version with the existing segments that are already stored. The server performs reverse deduplication as described in §3.2, including: loading metadata files and building the block fingerprint index on the fly, searching for duplicates and updating direct/indirect references, and removing duplicate blocks from segments via block punching or segment compaction.

Our RevDedup prototype is implemented in C in Linux. We use SHA-1 for both segment and block fingerprint computations. The RevDedup server mounts its data storage backend on a native file system. RevDedup requires that the file system support hole-punching, and here we use Ext4 for Linux. In the following, we address several implementation details.

Mitigating interference. Since a client may perform fingerprint computations for a running VM, minimizing the interference to the running VM is necessary. Here, we can leverage the snapshot feature that is available in today's mainstream virtualization platforms. The client can directly operate on the mirror snapshot in the background and destroy the snapshot afterwards.

Communication. The client-server communication of RevDedup is based on RESTful APIs, which are HTTP-compliant. A client can retrieve a VM image by issuing a correct HTTP request. The server can process multiple requests from different simultaneously.

Multi-threading. RevDedup exploits multi-threading to achieve high read/write performance. In writes, the server uses multiple threads to receive segment uploaded by the clients and perform reverse deduplication. In reads, the server uses dedicated threads to pre-declare the segment reads in kernel by using the POSIX function `posix_fadvise(POSIX_FADV_WILLNEED)`. With read pre-declaration, the kernel can make effective pre-fetching of segments to improve read performance.

In addition, the server uses a separate thread to trace the chains of indirect references of blocks when old versions are read. Once the direct reference is found, the thread sends the block address to another thread for reading the block content. Both threads run concurrently. This reduces the overhead of tracing long indirect reference chains.

Handling of null blocks. In practice, VM images contain a large number of null (or zero-filled) blocks [11]. In RevDedup, the server skips the disk writes of any null blocks appearing in the segments submitted by a client. When a null block is to be read, the server generates null data on the fly instead of reading it from disk.

3.4 Discussion

Conventional (inline) deduplication (e.g., in [23, 25, 31]) typically applies global deduplication to small-size data units and removes duplicates from new data. It is equivalent to setting a small segment size for global deduplication and disabling reverse deduplication in RevDedup. Conventional deduplication generally achieves higher backup throughput than RevDedup, since it can discard more duplicate segments on the client side with more fine-grained global deduplication, while RevDedup removes some duplicates on the server side via reverse deduplication. Nevertheless, RevDedup can still achieve high backup throughput if the client side discards enough duplicate segments with our coarse-grained global deduplication. On the other hand, conventional deduplication sees decaying read performance for newer data due to fragmentation. We compare both approaches in §4.

4 Evaluation

We conduct testbed experiments on RevDedup using different workloads, including unique data and two VM datasets. Our results are summarized as follows:

- RevDedup maintains high baseline throughput in unique data (§4.1).
- We show via real-world VM traces that RevDedup achieves: (i) high deduplication efficiency compared to existing deduplication approaches, (ii) high backup throughput given the available resources in the system, and (iii) high read throughput for restoring the latest versions of any VMs (§4.2).
- We show via a VM backup with a long version chain that: (i) RevDedup incurs small metadata overhead in the reverse deduplication process and can be configured between block punching and segment compaction during backup operations, and (ii) RevDedup incurs small overhead in tracing indirect references for earlier versions (§4.3).

Our experiments are conducted on a machine with a 3.4GHz Intel Xeon E3-1240v2 quad-core, eight-threaded processor, 32GB RAM, and a RAID-0 disk array with eight ST1000DM003 7200RPM 1TB SATA disks [26]. Since our testbed has only 8TB of raw storage, the actual memory usage of RevDedup in our experiments is much less than 32GB based on our calculations in §3.1.1 and §3.2.1. Also, we point out that RAID-0 is not recommended for fault-tolerant systems as it stripes data without parities, but we choose it in our experiments to maximize the disk array throughput for our stress tests. The machine runs Ubuntu 12.04 with Linux kernel 3.2.0.

We create eight client processes and one server process, all of which are executed on the same machine and are connected by the Linux loopback interface, so as to eliminate the network bottleneck for our high-performance benchmarking. The client processes submit VM data to the server concurrently.

We consider four segment sizes for global deduplication: 4MB, 8MB, 16MB, and 32MB. We fix the block size at 4KB for reverse deduplication to match the file system block size. We set the default rebuild threshold at 20% for our block removal mechanism.

We focus on examining the read/write performance of RevDedup. We exclude fingerprint calculations from our experiments. In real deployment, the clients can generate VM snapshots and compute fingerprints offline before connecting to the server. The fingerprint computations should not affect the actual read/write performance of RevDedup. In our experiments, we pre-compute all segment and block fingerprints before benchmarking. Our throughput results are averaged over five runs.

4.1 Evaluation with Unique Data

We measure the baseline performance of RevDedup using unique data. The server initially contains no data. The client processes submit 128GB of unique data (i.e., all blocks are globally unique) to the server. Then a client process retrieves the data using the Linux command `wget`. We also measure the raw disk throughput by reading/writing data directly via the native file system of our testbed.

Table 1 shows the results. The write throughput of RevDedup is 13-19% less than the raw write throughput, mainly because RevDedup needs to handle segment metadata including fingerprints and reference counts. When the segment size is larger, fewer segments are involved and RevDedup has higher unique write throughput. On the other hand, the read throughput of RevDedup is very close to the raw read throughput.

(GB/s)	Raw	4MB	8MB	16MB	32MB
Write	1.37	1.11	1.18	1.17	1.20
Read	1.27	1.26	1.27	1.27	1.25

Table 1: Throughput of RevDedup for unique data.

4.2 Evaluation with Real-World VM Usage

We evaluate RevDedup for backing up the disk states of multiple VMs based on real-world workloads.

4.2.1 Dataset

We collected a real-world dataset from the snapshots of VMs used by university students in a computer science programming course. We prepared a master image of size 7.6GB with 32-bit Ubuntu 10.04 installed. We then cloned 160 VMs, and assigned one to each student to work on three programming assignments in a semester. We generated 12 weekly versions for each VM, and computed a cryptographic hash for every 4KB block in each version. If no deduplication is applied, the total size of all versions over the 12-week span is 14.3TB. If we exclude null blocks, there is 6.67TB of data.

We first analyze the dataset to develop ground truths. Figure 5 shows the boxplots for the distributions of changes of each weekly version (from Week 2 to Week 12) with respect to the version of the same VM in the previous week. Each boxplot shows the minimum, lower quartile, medium, upper quartile, and maximum of all 160 versions each week. We note that most VMs have less than 100MB of changes per week. In Week 4, there is a spike of data changes due to an assignment deadline. Our dataset also contains outliers that generate significant data changes. For example, in Week 12, a student generates 6GB of new data (not shown in the figure).

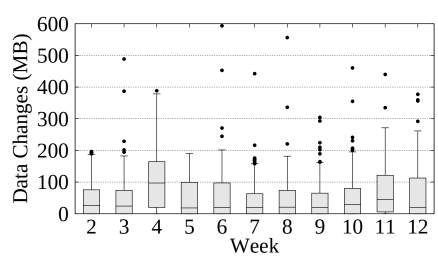
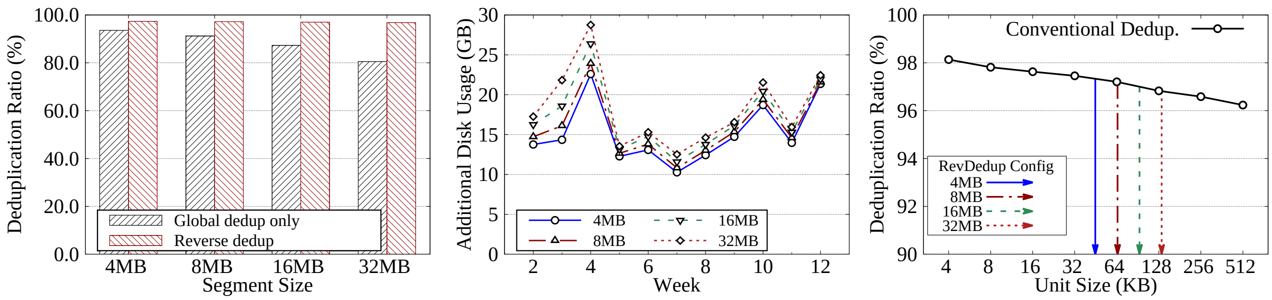


Figure 5: Boxplots of data changes (we only plot data within 600MB).



(a) Dedup ratios of reverse dedup and conventional dedup

(b) Additional disk usage for storing versions using RevDedup

(c) Dedup ratios of RevDedup and conventional dedup

Figure 6: Deduplication efficiency of RevDedup in real-world workloads.

4.2.2 Storage Efficiency

We evaluate the storage efficiency of RevDedup when storing the 12 weekly version sets. We measure the actual disk usage including both data and metadata.

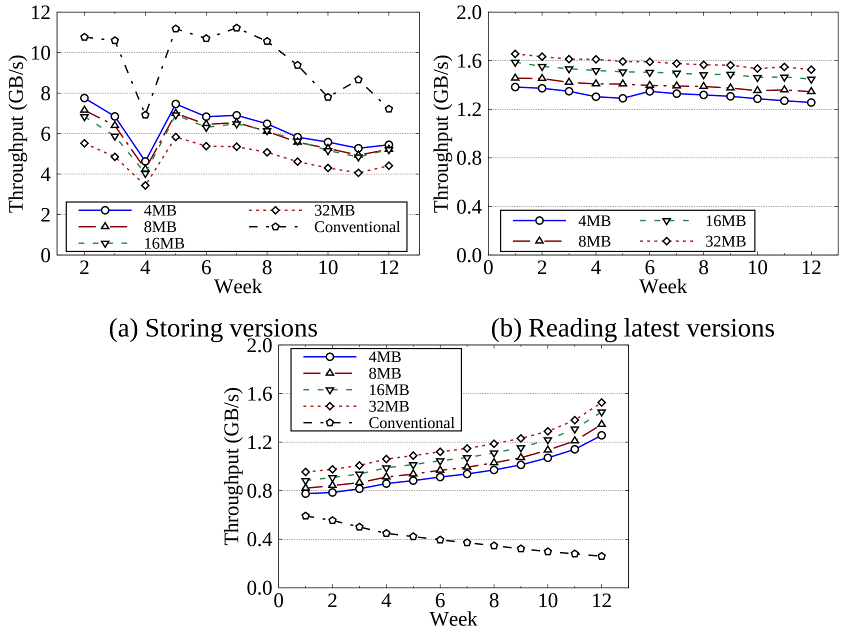
Effectiveness of reverse deduplication. We examine the storage savings of RevDedup using reverse deduplication (with 4KB block size). We define the *deduplication ratio* as the percentage of space saved with deduplication to the total size of all VM images (excluding null blocks) without deduplication. A higher deduplication ratio means higher storage efficiency. Here, we compare two variants of RevDedup: (i) only coarse-grained global deduplication is used, and (ii) both global and reverse deduplications are used. Figure 6(a) shows the deduplication ratios. Coarse-grained global deduplication itself achieves space saving of 80.5-93.6%, while reverse deduplication further removes duplicates and increases the saving to 96.8-97.3%. This saving is comparable to existing deduplication systems (see below). In the following experiments, we enable reverse deduplication in RevDedup.

Additional space usage per week. We now provide a more detailed analysis of the space usage of RevDedup for each weekly version set. Figure 6(b) shows the additional disk space for storing each weekly version set using RevDedup since Week 2. We see that the trend follows that of the change distributions shown in Figure 5 (e.g., large space usage in Week 4). Note that RevDedup introduces more additional space in Week 12 than in Week 11, although both weeks have similar change distributions (see Figure 5). The reason is that Week 12 has outliers that make significant changes. A key observation is that the additional space usage only increases marginally when the segment size increases from 4MB to 32MB.

Comparisons with conventional deduplication. We now compare the storage efficiency of RevDedup with conventional deduplication that operates on data units of small size (e.g., few kilobytes). Figure 6(c) plots the deduplication ratios. The various configurations of RevDedup have similar storage efficiency to the conventional approaches with data unit size ranging from 32KB to 128KB. The results indicate that RevDedup can achieve comparable storage efficiency to some state-of-the-art deduplication file systems. For example, ZFS [22] and Opendedup SDFS [21] operate on fixed-size units with default size 128KB.

4.2.3 Throughput

We compare the backup and read throughput of RevDedup for different segment sizes and that of conventional deduplication. To evaluate the latter, we configure RevDedup to use a 128KB segment size for global deduplication and disable reverse deduplication. As shown in §4.2.2, the 128KB segment size has comparable deduplication efficiency to RevDedup and is the default setting in some state-of-the-art deduplication file systems [21, 22]. We only modify the chunking configurations of RevDedup to resemble a conventional deduplication approach, while retaining other implementation features described in §3.3 (e.g.,



(a) Storing versions (b) Reading latest versions

(c) Reading earlier versions

Figure 7: Performance of RevDedup when storing/reading 12 weekly version sets.

multi-threading and handling of null blocks). This enables us to compare RevDedup and conventional deduplication under fair conditions.

Backup throughput. We evaluate the backup throughput of storing the 12 version sets. The server has no data initially. Then we submit the 12 version sets in the order of their creation dates. We measure the time of the whole submission operation, starting from when the clients submit all unique segments until the server writes them to disk and performs reverse deduplication (for RevDedup). We call `sync()` at the end of each write to flush all data to disk. Here, we plot the results starting from Week 2, in which RevDedup begins to apply reverse deduplication to the version sets being stored.

Figure 7(a) shows the average times needed for RevDedup and conventional deduplication to backup each version of a VM (which has 7.6GB of raw data). As discussed in §3.4, conventional deduplication has higher backup throughput than RevDedup, for example, by 30-65% compared to RevDedup with segment size 4MB. Nevertheless, RevDedup still achieves high backup throughput in the range around 4-7GB/s. Its backup throughput is higher than the raw write throughput by around 3-5× as it can discard the writes of a large number of duplicate segments on the client side (as shown from the storage saving of our coarse-grained global deduplication in Figure 6(a)). A smaller segment size implies higher throughput since more duplicates are discarded on the write path. Note that there is a throughput drop in Week 4 due to significant modifications made to the VMs (see Figure 5).

Read throughput. We evaluate the read throughput of RevDedup in two parts. We submit each of the 12 version sets in the order of their creation dates. After submitting a version set, we immediately retrieve all versions of that set (call it "reading latest versions"). After submitting all versions, we measure the time of reading each version set (call it "reading earlier versions"). Note that conventional deduplication has the same read throughput in both parts as it does not modify the earlier versions after they are stored (as opposed to RevDedup). Before each measurement, we flush the file system cache using the command "`echo 3 > /proc/sys/vm/drop_caches`".

Figure 7(b) shows the throughput of RevDedup in reading the latest versions. The overall read throughput of RevDedup is 1.2-1.7GB/s. The latest versions are only subject to segment-level fragmentation due to

coarse-grained global deduplication. For the version sets of later weeks, the read throughput drops as the degree of segment-level fragmentation increases, but the drop remains small. A larger segment size also gives higher read throughput as the fragmentation is better amortized. We point out that the read throughput of RevDedup is higher than the raw read throughput. The reason is that RevDedup generates null blocks of VM images on the fly rather than reading them from disk (see §3.3). We expect that as a VM ages, more null blocks will be filled with content and eventually RevDedup will see read throughput drop below the raw read throughput. Therefore, *we do not claim that RevDedup reads faster than raw read*. Nevertheless, the throughput drop is expected to be mild as we use a large segment size to amortize disk seeks.

Figure 7(c) shows the throughput of RevDedup in reading earlier versions after storing all versions. We also include the results of conventional deduplication here. We observe that RevDedup confirms our design goal, as the read throughput decreases with earlier versions being read. For example, the read throughput for Week 1 is up to 40% less than that for Week 12. The figure also shows the fragmentation problem in conventional deduplication. For Week 1, the read throughput can only achieve 606MB/s (at least 25% less than RevDedup), mainly due to fragmentation introduced in global deduplication with the small segment size at 128KB. The read throughput decreases further for later weeks. It drops to 266MB/s for Week 12, which is only around 20% of the raw read throughput (see Table 1). This shows that fragmentation becomes more severe for newer versions.

4.3 Evaluation with a Long-Chained VM

We now evaluate the metadata overheads of backup/read operations in RevDedup when the number of versions of a VM backup grows.

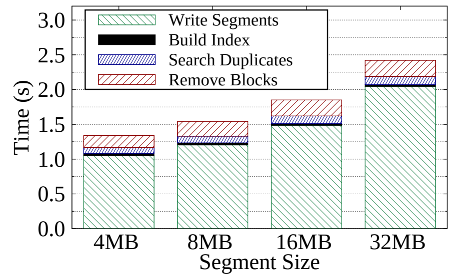
4.3.1 Dataset

The dataset was also used in the prior work [28]. We consider a Fedora 14 VM configured with 5GB disk space. The VM ran a cron job "`yum -y update`" to download and install updates daily. The updates modified the VM system files accordingly. The VM also ran other background maintenance jobs that may change the disk state, but did not generate any user data. We collected 96 daily versions of the VM. We find that the VM has around 50-100MB changes of data per day.

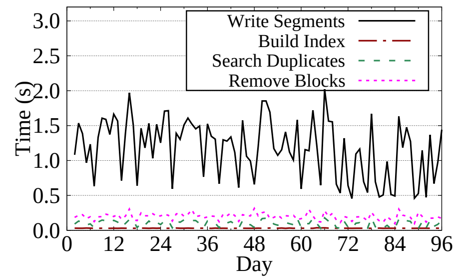
4.3.2 Backup Overhead

We evaluate the overhead of the backup operation in RevDedup. The server initially has no data. We submit the 96 daily versions to the RevDedup server in the order of their creation dates. Recall from §3.3 that the server performs several steps: (i) writing unique segments to disk and linking to existing segments, (ii) building the index, (iii) searching for duplicates, and (iv) removing duplicate blocks. Steps (ii)-(iv) correspond to the reverse deduplication overhead, which we evaluate here. In our measurements, we call `sync()` after writing unique segments to disk in Step (i).

Figure 8(a) shows the average time of writing a version, and provides a breakdown for different steps. Reverse deduplication (i.e., Steps (ii)-(iv)) accounts for only 15-22% of the total backup time. Specifically, block removal contributes to most of the running time in reverse deduplication, since it needs to copy data segments in segment compaction (if the percentage of removed blocks is above 20% as specified in our default setting). Figure 8(b) shows the instantaneous time of writing each version, with the segment size fixed at 32MB. The reverse deduplication overhead remains small compared to the backup operation during the entire period.



(a) Different segment sizes



(b) Different days (segment size is 32MB)

Figure 8: Backup time (per version) of RevDedup for a long-chained VM.

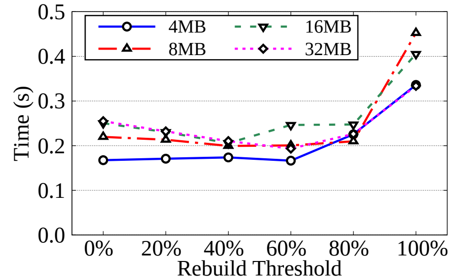
4.3.3 Block Removal Overhead

We evaluate the impact of different rebuild thresholds on block removal (see §3.2.4). We submit the 96 versions using different thresholds. Figure 9(a) shows the average time needed for RevDedup to perform block removal for each VM. Initially, the block removal time decreases with the threshold, since RevDedup uses block punching more frequently and incurs fewer I/Os of block content in segment compaction. However, the block removal time increases as the threshold further increases, since segment compaction has less overhead with fewer blocks being copied, while block punching removes more blocks and incurs higher file system metadata overhead. Overall, when the rebuild threshold is less than 80%, the block removal time is within 0.26s, which remains small compared to the overall backup time (see Figure 8).

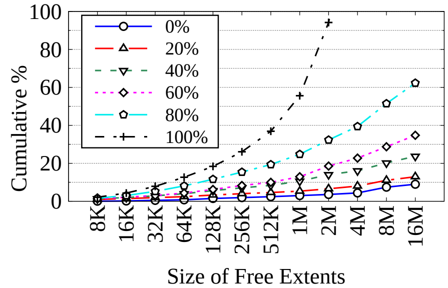
We also evaluate the impact on disk fragmentation for different rebuild thresholds. We use the Linux utility `e2freefrag` to report the percentage distribution of the sizes of free extents (i.e., the contiguous regions of free blocks) in the whole file system partition after storing all 96 versions. We normalize the percentage for each size range of free extents by dividing the total size of such free extents by the size of the actual data being stored (after deduplication). Here, we fix the segment size at 32MB. We say a free extent is small if its size is less than the 32MB segment size. A high percentage of small free extents means that the disk is more fragmented. Figure 9(b) shows the cumulative percentage distribution. A steeper curve implies that the degree of disk fragmentation is higher. The figure shows significant disk fragmentation when the threshold is at least 40%. When the threshold reaches 100% (i.e., block punching only), the cumulative percentage goes beyond 100%, meaning that the amount of small free extents is greater than the amount of stored data.

4.3.4 Read Overhead

Recall that reading a deduplicated block of an old version is done by tracing a chain of the indirect references. We now evaluate such tracing overhead. We submit all 96 daily versions in the order of their creation dates, and then read each version after all submissions. Here, we fix the segment size at 32MB. Figure 10 shows



(a) Block removal time per version



(b) Disk fragmentation distribution with segment size fixed at 32MB (we only plot data within 100%)

Figure 9: Effects of different rebuild thresholds in block removal.

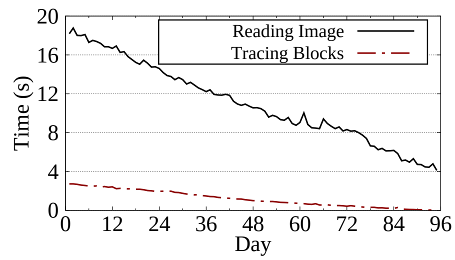


Figure 10: Tracing overhead of RevDedup for a long-chained VM (segment size is 32MB).

the overall time of reading each 5GB version and the time spent in tracing the indirect references for each version. We see that the tracing step only accounts for at most 15% of the overall reading time and has small overhead.

5 Conclusions

We present RevDedup, a deduplication system designed for VM disk image backup in virtualization environments. RevDedup has several design goals: high storage efficiency, low memory usage, high backup performance, and high restore performance for latest backups. The core design component of RevDedup is reverse deduplication, which removes duplicates of old backups and mitigates fragmentation of latest backups. We extensively evaluate our RevDedup prototype using different workloads and validate our design goals.

Availability. We plan to make the RevDedup software and our datasets available when the final version of the paper is published.

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